

Retraction

Retracted: Optimal Scheduling Model of WDM/OTN Network Transmission Line Based on Machine Learning

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation. The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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Research Article

Optimal Scheduling Model of WDM/OTN Network Transmission Line Based on Machine Learning

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In order to solve the problem that the influencing factors are difficult to parameterize in the design and development of WDM/ OTN backbone network routing planning tools, the author proposes an optimal scheduling model for WDM/OTN network transmission lines based on machine learning. Using the machine learning classification algorithm as a tool, the weight coefficients of each constraint factor are extracted from the historical design decisions, and the routing parameter model is constructed, so as to realize the intelligent routing selection, through actual simulation analysis and engineering verification. Simulation results show that after the historical routing regression test, the path coincidence rate of the route obtained by the algorithm and the historical real decision-making route reaches 81%, and the resource hit rate reaches 84%, which meets the requirements for actual production. *Conclusion*. This method can accurately and effectively generate network weight parameters so that the software routing is more intelligent.

1. Introduction

Since the 21st century, human society has gradually moved towards informatization, networking, and intelligence. Mobile Internet, 3D high-definition video, cloud computing, Internet of Things, and other technologies are gradually being integrated into people's daily life, and the scale of business needs is growing at a geometric rate. With the gradual implementation of the national "Broadband China" strategic project and strategic plan, the construction of broadband network infrastructure has entered a period of rapid development. The traditional voice service is not the main body of the communication network for a long time; the Internet technology based on digital services promotes the transfer of the traditional communication network traffic to IP; and the system architecture of the communication network has also changed from the circuit network to the "high-speed, large-capacity, integration," which is the development of "intelligent" packet-switched networks. This

poses a severe test for the technical upgrade of network hardware equipment and the software intelligence at the operation and management level. At present, the optical transport network (OTN) dominated by the wavelength division multiplexing (WDM)/optical transport network (OTN) as the basic bearer network provides a transparent and flexible bearing platform for large-granular business, data network, and mobile network. In the face of the continuous expansion of the optical transmission network scale and the continuous growth of network resource data, the speed and efficiency of manual network planning optimization and operation and maintenance have fallen into a bottleneck, and the software, tool and automation of network planning, and optimization have become imperative [1]. However, optical network planning, especially the routing selection and wavelength assignment of WDM/ OTN, needs to do multiobjective design for the whole network and configure it flexibly according to network resources and business conditions. How to make someone who does not have expert-level knowledge in communications, computer programmers who lack experience in network planning write programs that can closely integrate business and network development, network planning tool software that fully considers the overall thinking, and workflow and business requirements of network planning is a very practical and challenging problem.

2. Literature Review

MM Halldórsson et al. proposed a light performance monitoring based on a deep neural network model, a simple approach taken to preprocess the link between the training dataset and the specified operating range [2]. Song et al. proposed a new method for network traffic prediction based on deep learning. This method considers the correlation of data stream characters and space and time and uses the prediction model of denoising autoencoder (DAE) to learn general network traffic characteristics and then train it in a greedy hierarchical fashion [3]. Lin et al. pointed out that in the traditional research on network traffic, the convolutional neural network (Recurrent Neural Network, RNN) method only uses a single-dimensional time series of traffic as input, Because of the one-sidedness of the prediction results, it is proposed that the attribute information of the flow time series can be used to influence the prediction accuracy [4]. Hanson and Dougan proposed a machine learning method based on deep neural network, which predicts the power dynamics of a channel, ROADM (Reconfigurable Optical Add-Drop Multiplexer) system, through data acquisition and training. It is further concluded that the trained deep neural network can recommend wavelength assignment with minimum power offset for wavelength conversion [5]. Huang et al. investigated a machine learning technique that predicts whether the bit error rate of an unfixed optical path meets a desired threshold based on traffic, desired path, and modulation format. The system is trained and tested on synthetic data [6].

The author proposes to use machine learning classification algorithm as a tool, the weight coefficient of each constraint factor is extracted from the historical design decision, and the routing parameter model is constructed, so as to realize the intelligent routing selection.

3. Research Methods

3.1. Brief Analysis of Backbone Transport Network Routing Planning. Backbone transport network planning is usually a decision-making process under the conditions of multiple constraints and multiple demands [7]. The constraints of the planning work are reflected in the network transmission technology, existing network topology, and capacity limitations, which will restrict the configuration of service circuits. Demand is reflected in that network planning and construction are service-driven, and the fundamental purpose of circuit planning is to meet the needs of bearer users. As shown in Figure 1, if the planning process is regarded as a decision function, then the constraints of the network and business requirements can be passed in as input parameters, and the output of the decision function is the optimization or optimal network planning.

Generally speaking, the constraints in the planning process mainly include technical constraints, existing network topology constraints, physical constraints, and economic and policy constraints. In addition, network planning will also be affected by the actual needs of the business, including bandwidth requirements, protection methods, and QoS [8].

In routing selection and resource allocation, network cost or other performance parameters (such as scalability and reliability) are usually used as the objective function, and the final routing planning decision should be to satisfy the transmission demand with the minimum cost under the given constraints. However, it is sometimes difficult to quantify all technical standards and design constraints. For a network with a complex structure and an overly idealized automatic planning and design scheme, often the planning problem will get multiple solutions that satisfy the conditions [9]. In addition, the actual routing planning decisions often depend on the experience of the designers, and the decision-making process is difficult to be conveyed to the software developers accurately and in detail, and it is difficult to be abstracted into a logical program. Therefore, in the design and development process of such software, it is inevitable to encounter a situation where design decisions are difficult to software, and there is an "information gap" between software developers and network designers.

3.2. Resource Data and Historical Routing Data of Backbone Transport Network. Generally speaking, the resource data of the backbone transport network can be divided into three layers: the transmission station layer, the multiplex section layer, and the wavelength layer.

In addition to basic resource data, it is also necessary to establish a set of data structures for describing business requirements and planning results, which should include at least the following parts:

- (1) Service Optical Path Requirements. The optical channel service requirements of large service particles in the backbone network mainly including the optical channel number, starting node office, bandwidth requirements, protection methods, and service types.
- (2) *Routing*. A routing object corresponds to a complete planned link, but it does not describe the content of the specific routing link, but only describes the basic information of the route mainly attributes such as whether the optical channel to which it belongs is a working route or a protection route.
- (3) *Routing Link Segment* [10]. It describes a segment of a link in a route, including attributes such as the route to which it belongs, the link sequence number, and the channel used.

3.3. Preprocessing of Network Data. In order to transform the resource data, demand data, and planning result data of the network into samples suitable for machine learning, it needs to be preprocessed. As shown in Figure 2, the author



FIGURE 2: Composition of sample data.

proposes to use raw data to generate two types of sample data: topology impact samples and resource impact samples.

Among them, topological influence samples mainly describe the influence of topological characteristics such as link length and natural terrain on decision-making, with topological features as attributes and selection results as classification labels [11]. Figuratively speaking, topological influence can be analogized to the characteristics of road direction, length, and slope in road traffic, that is, "where to go."

The resource impact sample mainly describes the impact of resource characteristics such as bandwidth, idle channel ratio, device switching difficulty, cross-domain cost, and whether the channel needs to be split on decision-making in the link, category labels. Resource impact can also be compared to road traffic, which is equivalent to choosing what mode of transportation to go after selecting "what direction to go," that is, "how to go."

Based on the above classification principles, combined with the guiding ideology of parameterizing the routing decision of planners, this topic proposes data preprocessing according to the following ideas:

- (1) The fiber multiplexing section of each link of the historical route corresponds to a set of sample data, and the sample contains the business demand data of this decision and the resource information of the fiber multiplexing section, which is used as the attribute of the resource impact sample. Since the fiber multiplex section is finally selected for routing, the classification label is set to 1.
- (2) For each multiplex section that has not been selected under the same station section, it is also organized into a set of resource impact samples, and its classification label is set to 0, indicating that it has not been selected [12].
- (3) The station segment of each link of the historical route corresponds to a set of sample data, and the sample contains the service demand data of the decision and the topology information of the link and takes this as the attribute of the classified sample. Since the office station is finally selected for routing, the classification label is set to 1.

(4) Assuming that the starting end of the station segment selected in (3) is station A, and the end station is station B, then when routing to station A, there will be one or more station segments that can be selected as the next station, with one hop link, and each unselected station segment can generate a set of topology impact samples, and its classification label is set to 0 [13].

Taking the network data of China Mobile's 11th phase project as an example, several typical influencing factors are selected for data preprocessing, and the table structures of topology impact samples and resource impact samples are shown in Tables 1 and 2:

3.4. Machine Learning Classification Model Simulation and Performance Analysis

3.4.1. Basic Principles and Model Construction of Naive Bayes Classifier. Bayes classifier (Bayes classifier) is a classifier based on Bayesian decision theory, which is a typical algorithm for implementing decision under the probability framework [14]. The basic idea is based on samples and classification labels and uses Bayes' theorem to solve a parametric model that maximizes the posterior probability.

Assuming that there are N possible classification labels, denoted as $Y = \{c_1, c_2, \ldots, c_N\}$, and that the sample is denoted as x, the Bayesian classifier that maximizes the posterior probability is as follows:

$$h_b^*(x) = \operatorname*{arg\,max}_{c \in r} P(c|x). \tag{1}$$

In practical applications, samples are often assumed to have "attribute independence"; therefore, the solution of the joint conditional probability can be simplified to the product of the conditional probability of each attribute, which is the naive Bayes classifier.

Based on naive Bayesian classifiers, probabilistic parametric models for topology decisions and resource decisions for wavelength routing can be constructed [15, 16]. The continuous data are discretized by the unsupervised equaldepth binning method, and then the sample data is calculated by the naive Bayesian classification algorithm, which can obtain all attributes and classification labels corresponding to $P(x_i|c)$ and P(c). Table 3 shows the parametric model of the topological influence factor distance ratio (DIST_RATIO).

It can be seen that with the increase of the distance ratio, $P(x_i|c=0)$ shows a downward trend, while $P(x_i|c=1)$ shows a decreasing trend, which is also consistent with the actual planning idea: If the next hop decision makes the route go far away from the end point of the service path, then this decision is likely to be unreasonable and not adopted. Similarly, other attributes can also be analyzed in the same way; thus, a complete probabilistic parameter model is constructed [17].

3.4.2. Basic Principles and Model Construction of Decision Trees. Decision tree algorithm is an inductive learning algorithm based on sample examples, which induces a set of classification rules based on tree structure representation

TABLE 1: Example of topology impact samples.

Transfer across devices	Whether to split the channel	Channel occupancy ratio	Category labels
0	1	0.9375	0
0	0	0.1813	0
0	1	0.8066	1
0	1	0.8487	0
0	0	0.1250	0

TABLE 2: Examples of resource impact samples.

Distance ratio	Whether across regions	Category labels
0.6475	0	0
0.5096	0	1
0.6725	0	0
0.7049	0	0
0.6069	0	0

 TABLE 3: Naive Bayes classifier parameter model for distance ratio (DIST_RATIO).

x_i attribute value	С	<i>P</i> (<i>c</i>)	$P(x_i c)$
[0, 0.3219]			0.4440
(0.3219, 0.6313]	0	0 0002	0.2473
(0.6313, 0.9406]	0	0.0003	0.1961
(0.9406, 1]			0.1126
[0, 0.3219]			0.1501
(0.3219, 0.6313]	1	0 1117	0.2064
(0.6313, 0.9406]	1	0.1117	0.2526
(0.9406, 1]			0.3909

from an unordered sample set. Each nonleaf node of the decision tree corresponds to an attribute test, and each child node corresponds to a classification result [18]. The sample set contained in each nonleaf node is divided into corresponding child nodes according to the test judgment result of this node. Typical decision tree algorithms are ID3, C4.5, and CART.

Based on the decision tree algorithm and integrated postpruning algorithm, a decision tree model for topology decision and resource decision of wavelength routing can be constructed.

3.4.3. The Basic Principle and Model Construction of Logistic Regression Classifier. Logistic regression classifier belongs to the generalized linear regression model, and although the name contains the word "regression," its essence is a binary classification algorithm [19]. The logistic regression classifier has a very concise algorithm:

$$h_{\theta}(\mathbf{x}) = g(\mathbf{\theta}^{T}\mathbf{x}) = \frac{1}{1 + e^{-\mathbf{\theta}^{T\mathbf{x}}}}.$$
 (2)

For a set of samples *x*, it is input into the classification function $h_{\theta}(\mathbf{x})$. If the output is greater than 0.5, the sample is classified as 1; otherwise, it is classified as 0. The construction method of the logistic regression classifier is to find the feature parameter vector θ [20].

TABLE 4: Logistic regression classifier parameter model.

Parameter	X_DEV	IS_SPLIT	WAVE_VLD [0, 0.3219]	WAVE_VLD (0.3219, 0.6313]	WAVE_VLD (0.6313, 0.9406]	WAVE_VLD (0.9406, 1)	Intercept
$\theta_{\mathbf{r}}$	-0.6316	0.0902	-0.7238	-0.6340	0.8509	3.6675	1.1203

TABLE 5: Comparative analysis of the characteristics of three classification algorithms.

Algorithm	Advantage	Disadvantage	Compatibility with routing plan
Naive Bayes classifier	Low operation cost, support incremental operation, and strong interpretability	Not suitable for strongly associated properties	Higher, and the probability-based routing mechanism will be adopted later.
Decision tree	Easy to extract rules, easy to visualize, and fast to test	Cannot be parameterized and easy to overfit	Not suitable, and it is difficult to cooperate with the routing mechanism
Logistic	Low computational cost, simple		Higher, and the routing mechanism
regression	implementation, and strong interpretation of	May underfit	based on edge weight will be adopted
classifier	results		later.

Based on the logistic regression algorithm, the gradient descent method is used to obtain the characteristic parameter vector θ . The logistic regression classifier model for the topology decision and resource decision of wavelength routing can be constructed, as shown in Table 4.

The parameter model is the characteristic parameter vector θ_r of resource impact. It can be clearly seen from the above table that the values of factors such as the need for equipment switching, the need to split wavelengths, and the low channel idle rate are all negative numbers, indicating that if the value of these attributes is 1, it is helpful for classification as 0 [21]. Corresponding to the actual engineering route selection, these factors will cause additional equipment costs, and the planning and design personnel will try to avoid this situation.

4. Results Analysis

4.1. Algorithm Performance Analysis. The advantages and disadvantages of the three classification algorithms and their fit with the backbone transport network routing planning are shown in Table 5.

It can be seen from the above results that although the overall performance of the decision tree is better than the other two algorithms, the decision tree algorithm itself does not fit well with the backbone transport network routing algorithm, so it should not be used [22]. Although the logistic regression classification model has certain advantages over the naive Bayesian classification model in the network data of China Mobile's eleventh phase project, the difference between the two is not large, and the model can be selected flexibly according to the actual performance.

4.2. Parametric Model Testing and Results

4.2.1. Application of the Parametric Model. After the parametric model is constructed, the parametric model can be used, and routing planning and resource allocation are based on probability or edge weights. For example, build a logistic regression classifier parametric model, and then leverage the topology to influence the parameters, and then

based on the KSP algorithm, several alternative routes are calculated, and the topological influence parameters and resource influence parameters are used to obtain the sum of the objective functions for each route so as to select the route that maximizes the function as the result route.

4.2.2. Test Methods and Results. Under the actual network data, the above modeling scheme is used to build a parameter model, which completely simulates the network environment and demand environment of the preengineering project and performs historical routing rearrangement, and the obtained results are compared with the historical real routing results, and two indicators of resource hit rate are used to evaluate the verification results.

The path coincidence rate is defined as

$$R_l = \frac{N_{L \cap L'}}{N_L}.$$
(3)

In formula (3), $N_{L \cap L'}$ represents the number of link segments of the central office where the software routing result coincides with the historical route, and N_L represents the number of link segments of the central office as the result of the system routing.

The resource hit rate is defined as

$$R_r = \frac{N_{R \cap R'}}{N_{L \cap L'}}.$$
(4)

In formula (4), $N_{R \cap R'}$ represents the number of resource hits in the overlapping station segment, and $N_{L \cap L'}$ represents the number of the overlapping station segment. Based on the engineering data of China Mobile's 9–11 backbone transmission network, according to the parameter model construction method described by the author, combined with the effective routing algorithm, the results obtained through the above verification methods are shown in Figure 3. After the historical routing regression test, the path coincidence rate of the route obtained by the algorithm and the historical real decision-making route reaches 81%, and the resource hit rate reaches 84%, which meets the requirements for actual production.



FIGURE 3: Accuracy of historical route rearrangement.

5. Conclusion

Aiming at the difficulty of parameterization encountered in the development process of the WDM/OTN backbone transport network routing planning and design software platform, the author proposes a routing parameter model construction method based on the machine learning classification algorithm. Verified by actual engineering data and combined with the analysis and evaluation of professional designers, this method achieves a high degree of fit between the software routing planning logic and the designer's decision-making process, which can basically replace the traditional manual routing work and greatly improve the efficiency of network planning work. Moreover, considering the feature that machine learning can make parameter models iteratively optimize, this method helps to improve the intelligence of the planning software platform and the efficiency of the development process.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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